High Resolution Spectral Mixture Analysis of Urban Reflectance

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Research

Urban Vegetation
Energy/Mass Flux Scaling
Reflectance Characteristics

Application

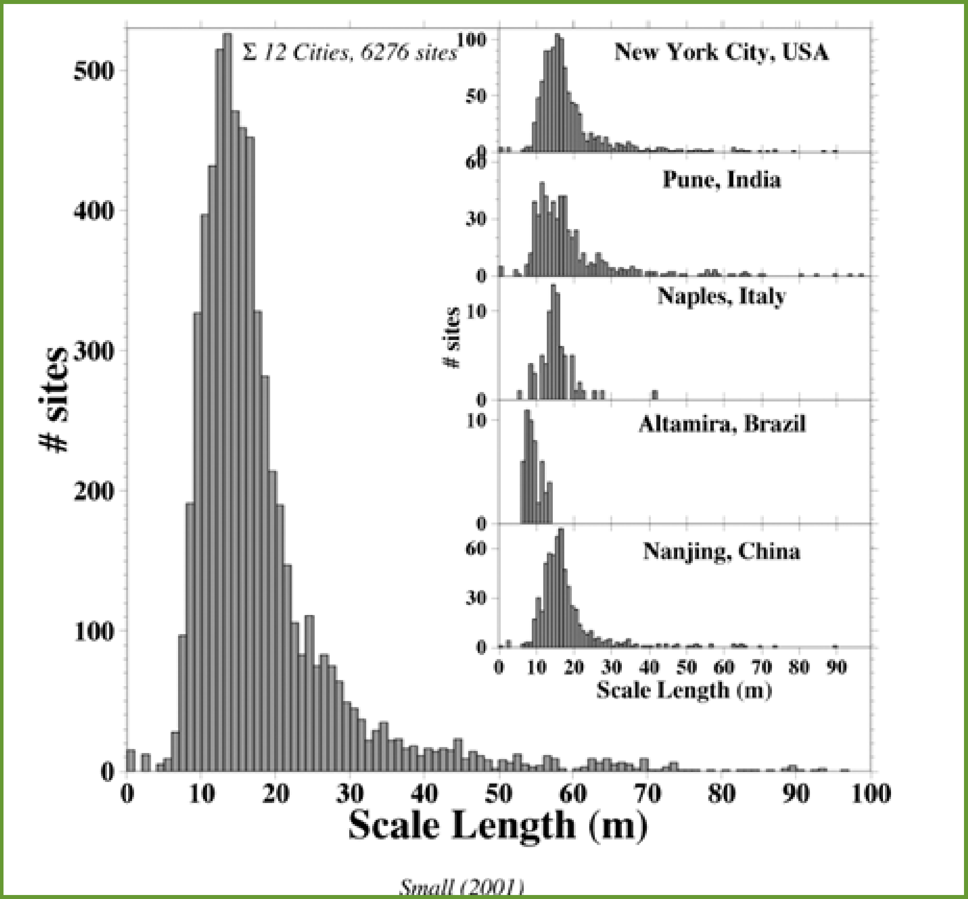
Urban Ecology
Urban Microclimate
Urban Growth Monitoring

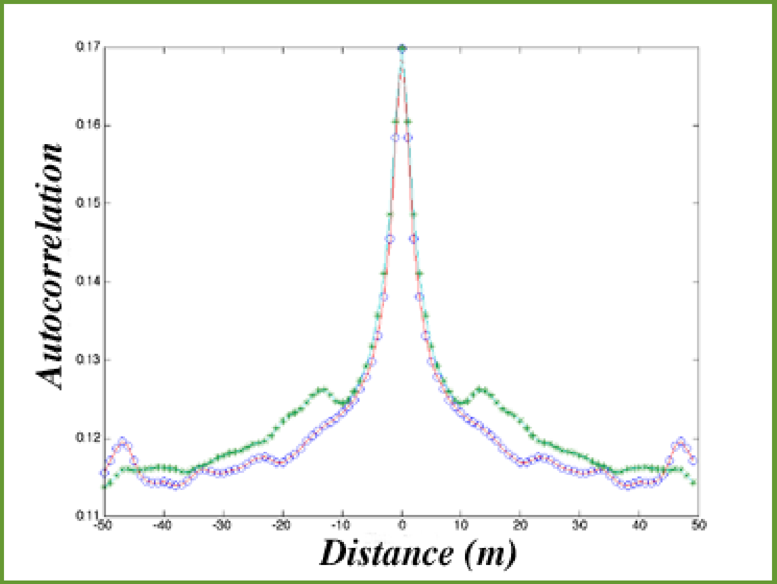
LAMONT-DOHERTY EARTH OBSERVATORY
OF COLUMBIA UNIVERSITY

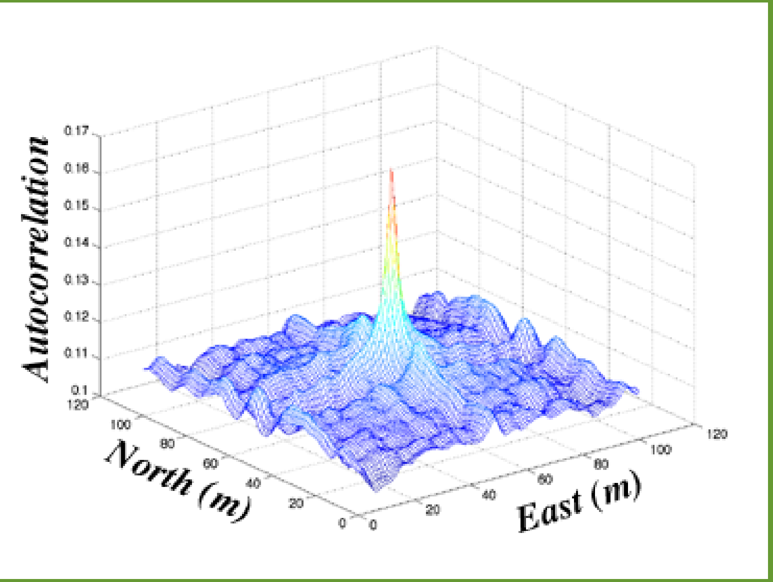
SEDAC

Spatial Autocorrelation of Ikonos pan gives estimates of characteristic scales of urban spectral heterogeneity.

10 - 20 meters







Spectral Mixture Analysis

Physical representation of spectrally mixed pixels as combinations of spectrally pure endmembers

Based on observation that radiances often mix linearly in proportion to area - to first order.

Given some knowledge of the spectral endmembers, it is possible to define a mixing space.

If the mixing among endmembers is linear it can be described with a system of linear mixing equations.

The number of resolvable endmembers is limited by the number of spectral bands.

The system of linear mixing equations can be inverted for endmember abundance fractions.

Spectral reflectance can be described as a linear combination of endmember spectra as:

$$f_1\mathbf{E}_1(\lambda) + f_2\mathbf{E}_2(\lambda) \ldots + f_n\mathbf{E}_n(\lambda) = \mathbf{R}(\lambda)$$

$\mathbf{R}(\lambda)$ is the observed reflectance profile, a continuous function of wavelength λ.
$\mathbf{E}_i(\lambda)$ are the endmember spectra and
f_i are the corresponding fractions of the n endmembers

Continuous reflectance profiles are represented as vectors of discrete reflectance estimates at specific wavelengths as:

$$\mathbf{E}(\lambda) = [e_{\lambda 1}, e_{\lambda 2} \ldots e_{\lambda n}] \quad \text{and} \quad \mathbf{R}(\lambda) = [r_{\lambda 1}, r_{\lambda 2} \ldots r_{\lambda n}]$$

$r_{\lambda i}$ represents a portion of the observed reflectance spectrum
$\mathbf{R}(\lambda)$, integrated over a finite spectral band with a center wavelength λ_i and
$e_{\lambda i}$ represents observed reflectance from the corresponding endmember $\mathbf{E}(\lambda)$.

The continuous linear mixing model can be represented in discrete form as a system of linear mixing equations

$$f_j\mathbf{e}_{ij} = \mathbf{r}_i \qquad i = 1,b \quad \text{and} \quad j = 1,n$$

The system of b linear equations can be written as:

$$\mathbf{Ef} = \mathbf{r}$$

The overdetermined linear mixing model, incorporating measurement error:

$$\mathbf{r} = \mathbf{Ef} + \varepsilon$$

ε is an error vector which must be minimized to find the fraction vector $\mathbf{f}$ which gives the best fit to the observed reflectance vector $\mathbf{r}$. Since $\varepsilon = \mathbf{r} - \mathbf{Ef}$, we seek to minimize:

$$\varepsilon^T\varepsilon = (\mathbf{r} - \mathbf{Ef})(\mathbf{r} - \mathbf{Ef}).$$

In the case of uncorrelated noise, the well known least squares solution is given by:

$$\mathbf{f} = (\mathbf{E}^T\mathbf{E})^{-1}\mathbf{E}^T\mathbf{r}$$

3 Endmember Linear Mixing Model

$$\begin{array}{lclclcl}
f_1\mathbf{E}_{1\lambda 1} & & f_2\mathbf{E}_{2\lambda 1} & & f_3\mathbf{E}_{3\lambda 1} & & R_{\lambda 1} \\
f_1\mathbf{E}_{1\lambda 2} & & f_2\mathbf{E}_{2\lambda 2} & & f_3\mathbf{E}_{3\lambda 2} & & R_{\lambda 2} \\
f_1\mathbf{E}_{1\lambda 3} & + & f_2\mathbf{E}_{2\lambda 3} & + & f_3\mathbf{E}_{3\lambda 3} & = & R_{\lambda 1} \\
f_1\mathbf{E}_{1\lambda 4} & & f_2\mathbf{E}_{2\lambda 4} & & f_3\mathbf{E}_{3\lambda 4} & & R_{\lambda 4} \\
f_1\mathbf{E}_{1\lambda 5} & & f_2\mathbf{E}_{2\lambda 5} & & f_3\mathbf{E}_{3\lambda 5} & & R_{\lambda 5} \\
f_1\mathbf{E}_{1\lambda 6} & & f_2\mathbf{E}_{2\lambda 6} & & f_3\mathbf{E}_{3\lambda 6} & & R_{\lambda 6}
\end{array}$$

To first order, radiances mix linearly in proportion to area.

Given some knowledge of the spectral endmembers (E), it is possible to* estimate *fractions (f) contributing to a spectrally mixed radiance measurement (R).

Questions

Topology

How does Ikonos represent spectral mixing spaces?

Dimensionality

How many dimensions are required?

Spectral Endmembers

Consistent endmembers for all urban areas?

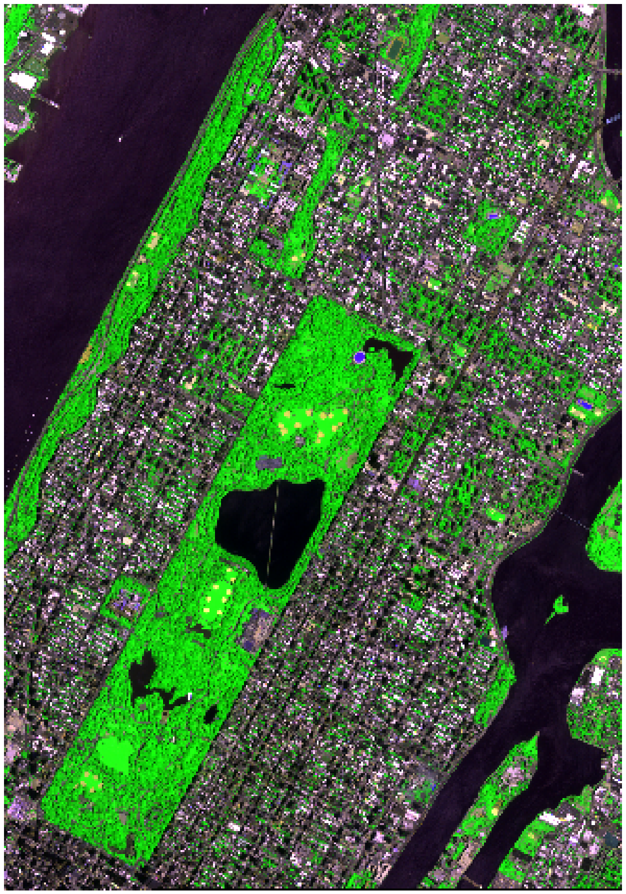
Linear Mixing

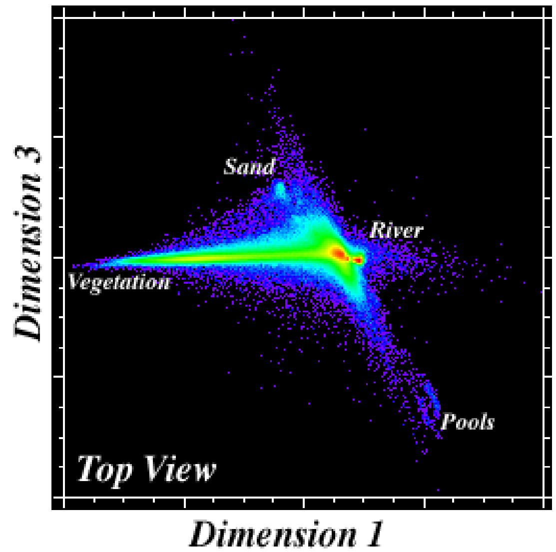
How nonlinear?

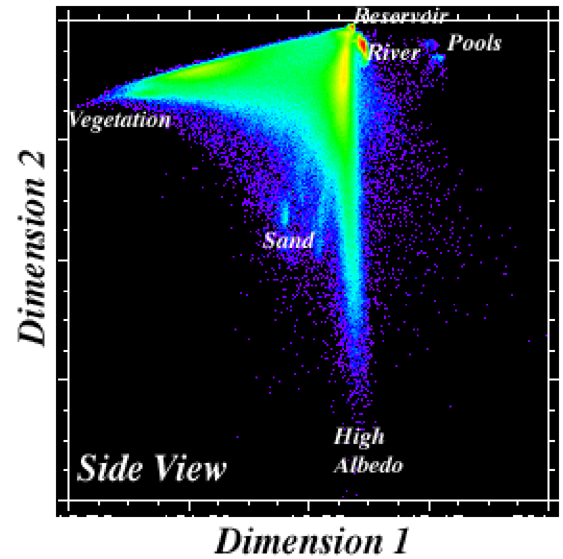
Applications

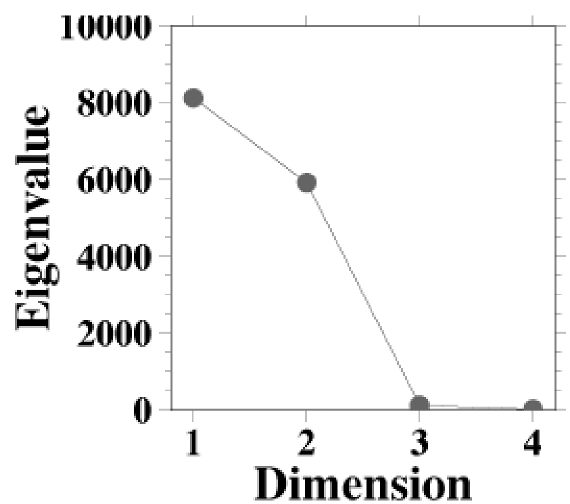
What can this be used for?

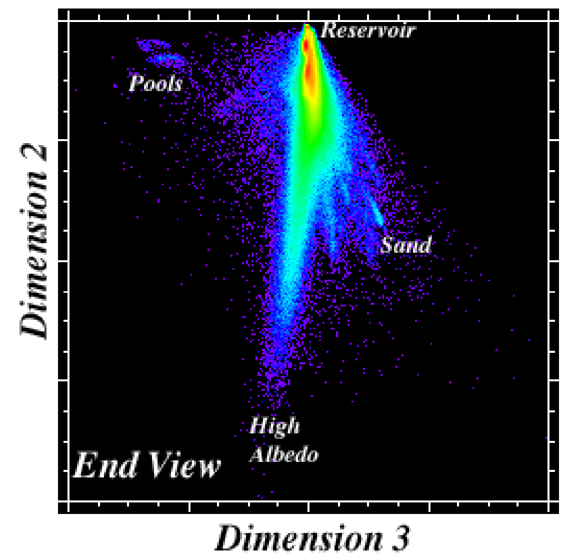
New York   7/3/01



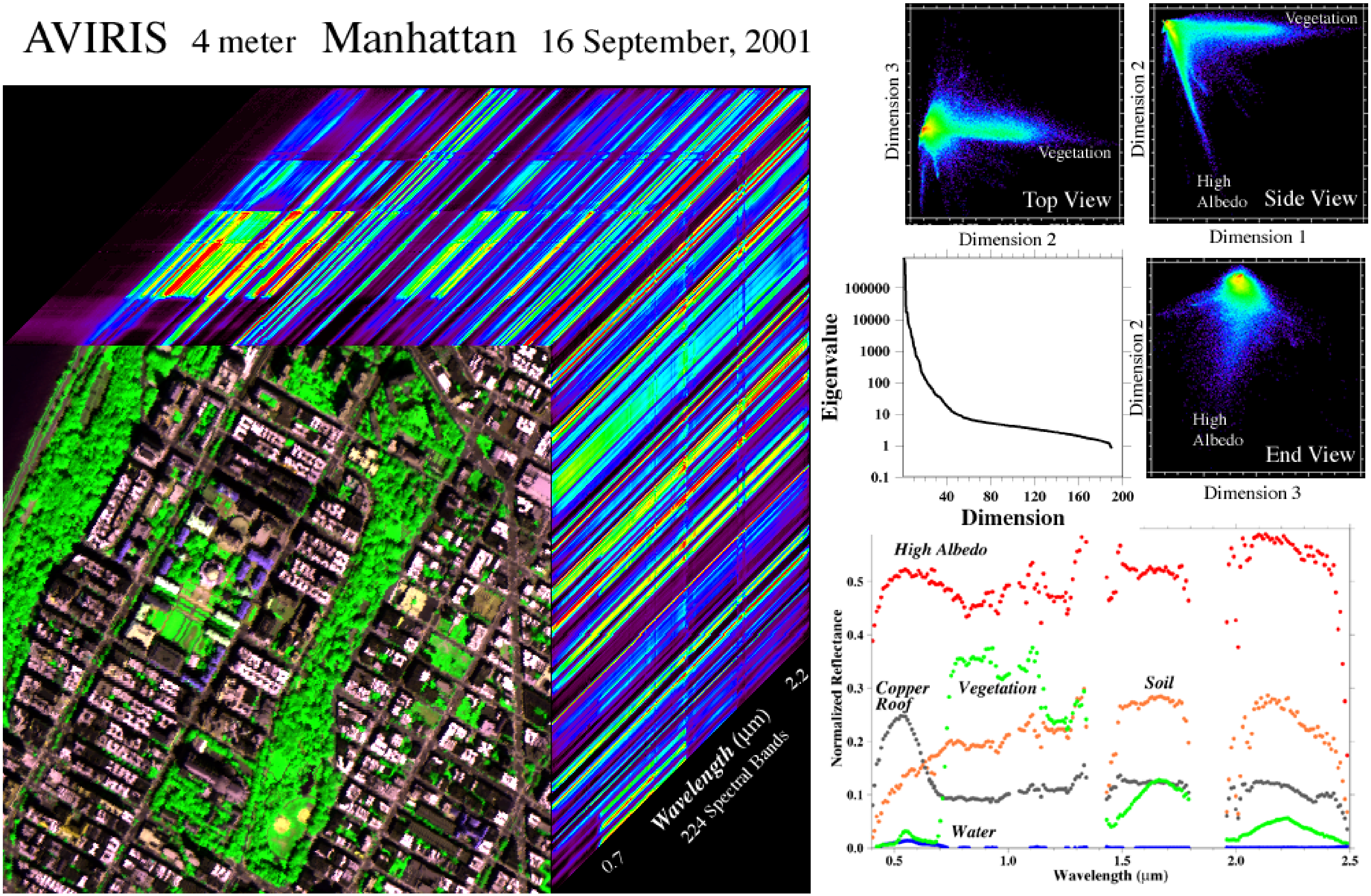




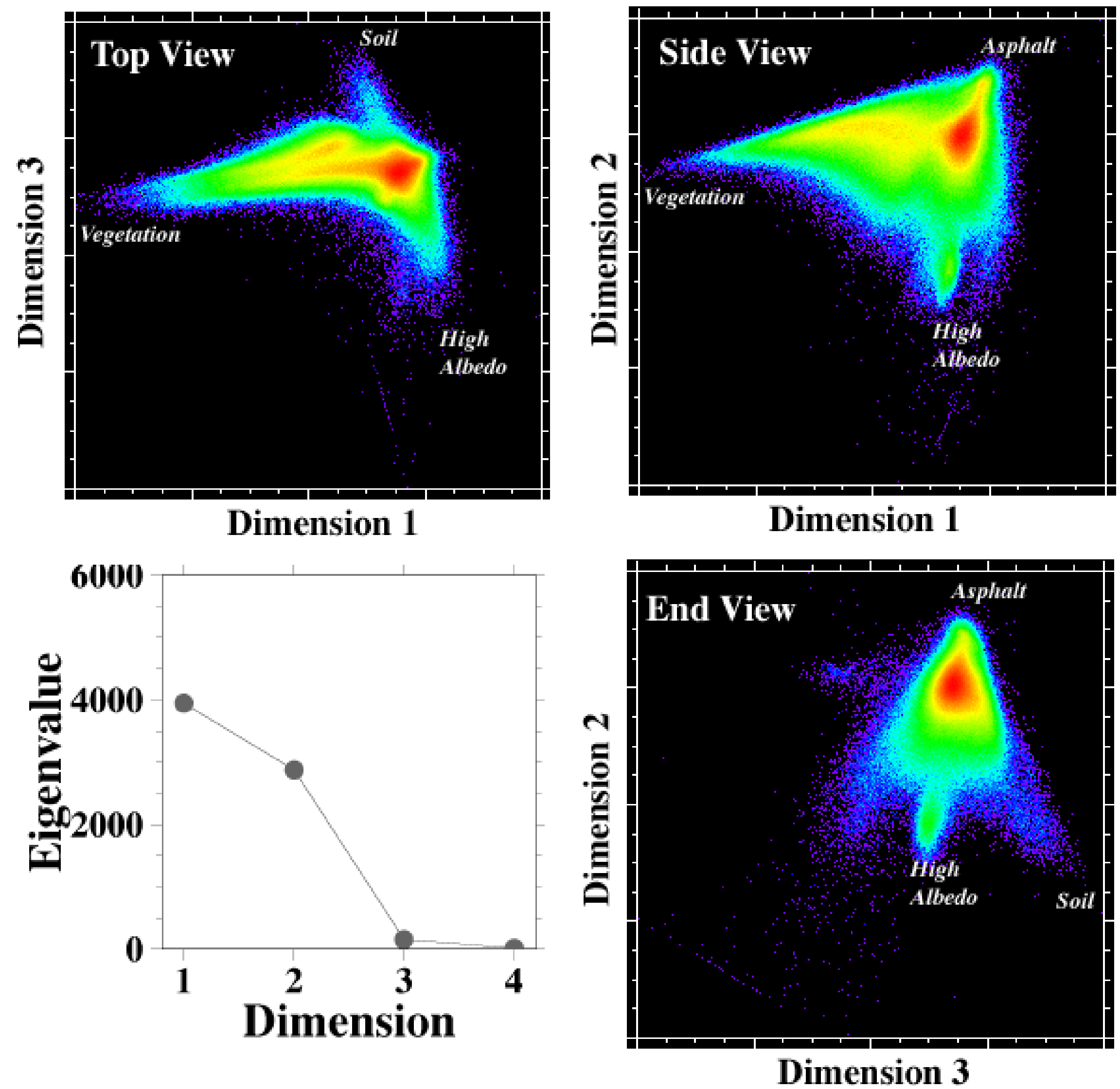




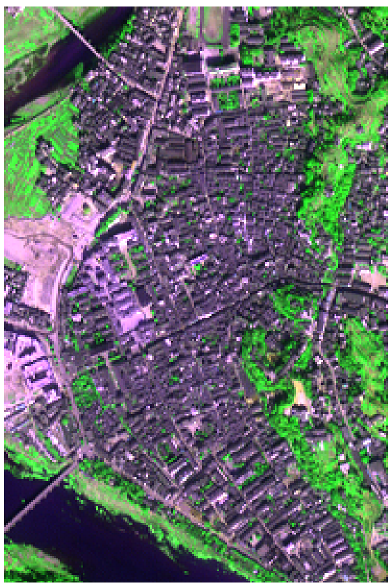
AVIRIS 4 meter Manhattan 16 September, 2001

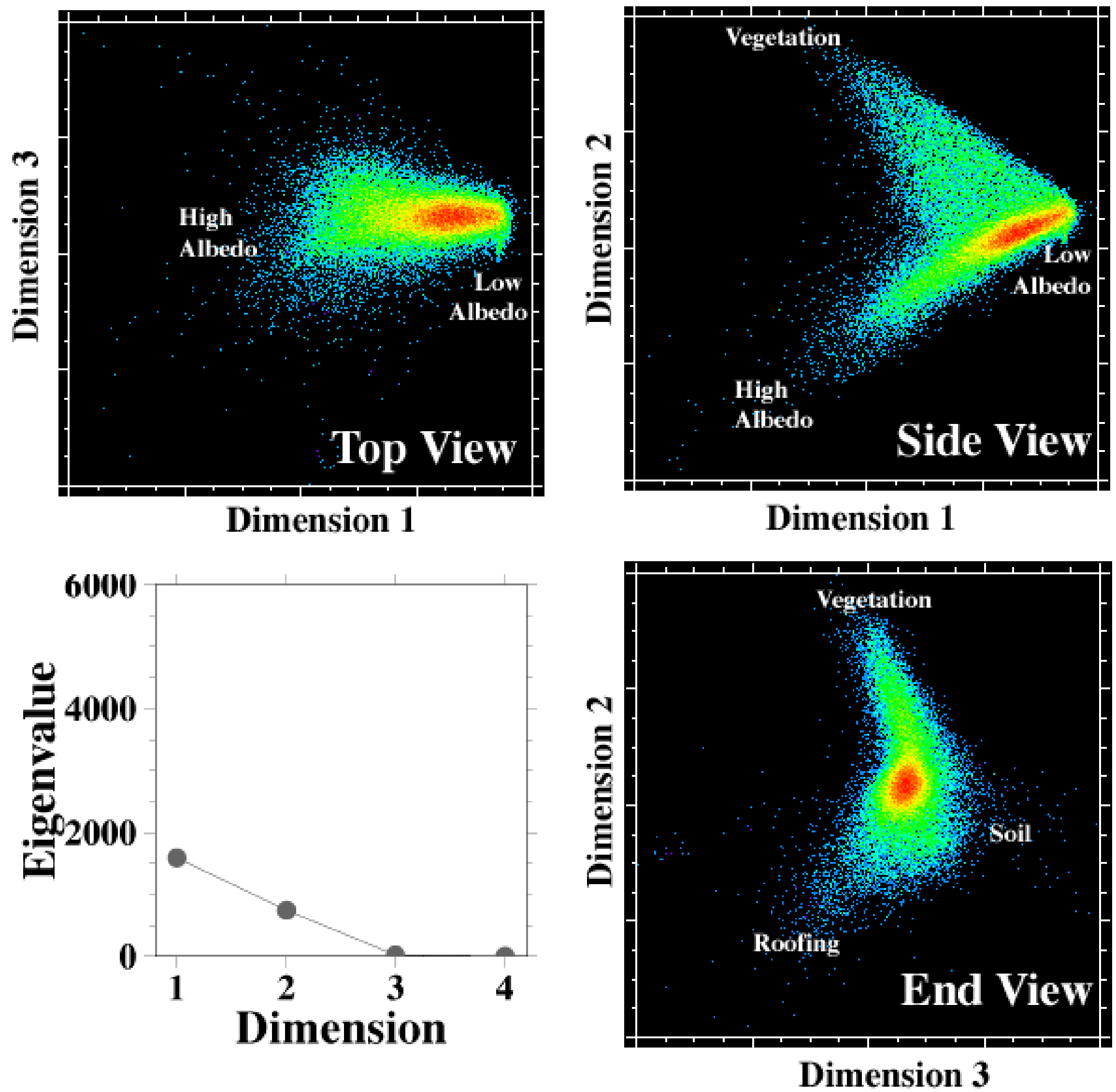


San Salvador 3/24/00

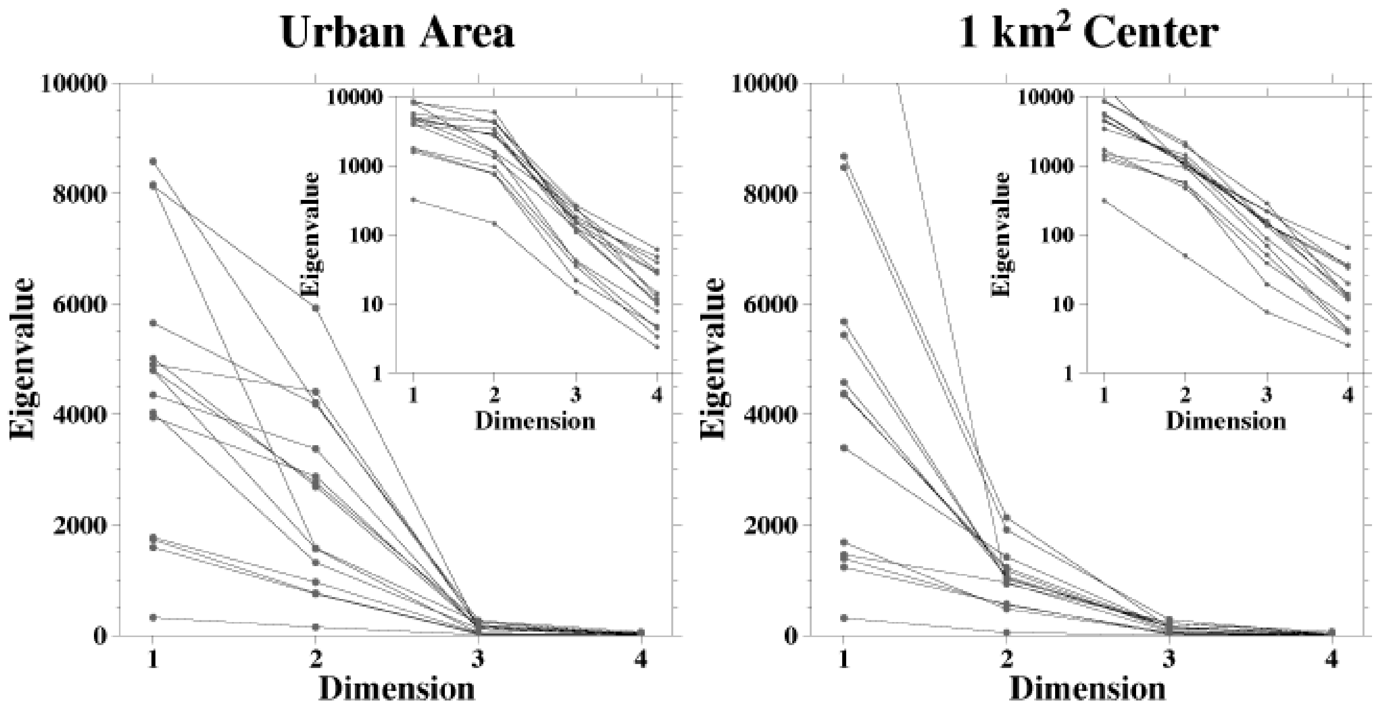


Somewhere in China

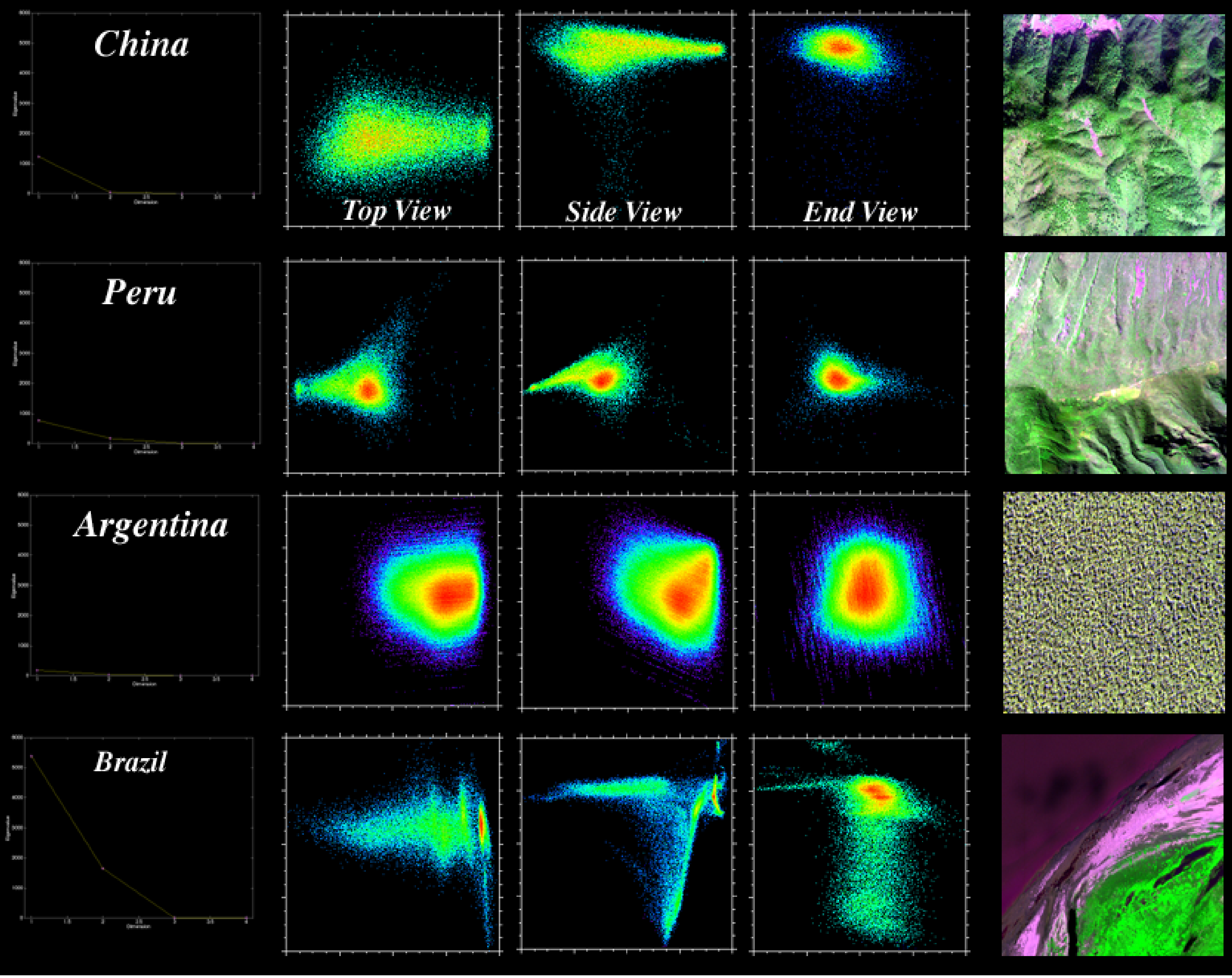




Urban spectral dimensionality is scale dependent.

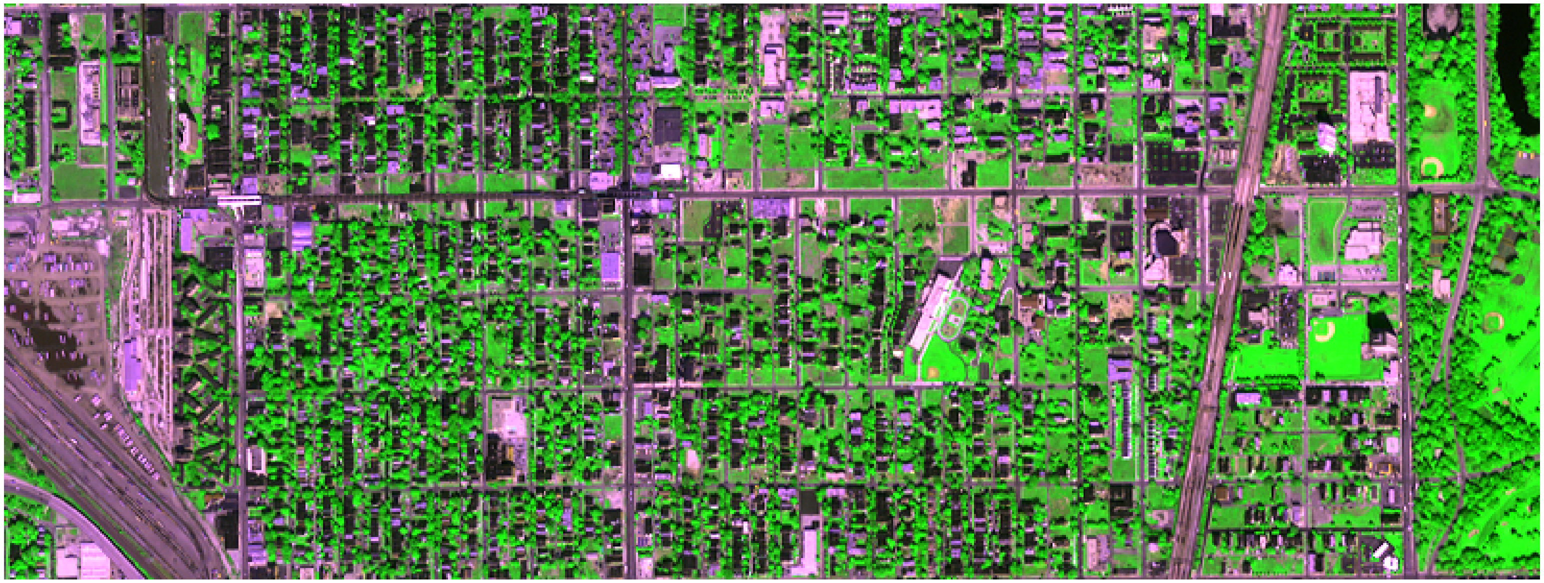


Non-Urban Environments

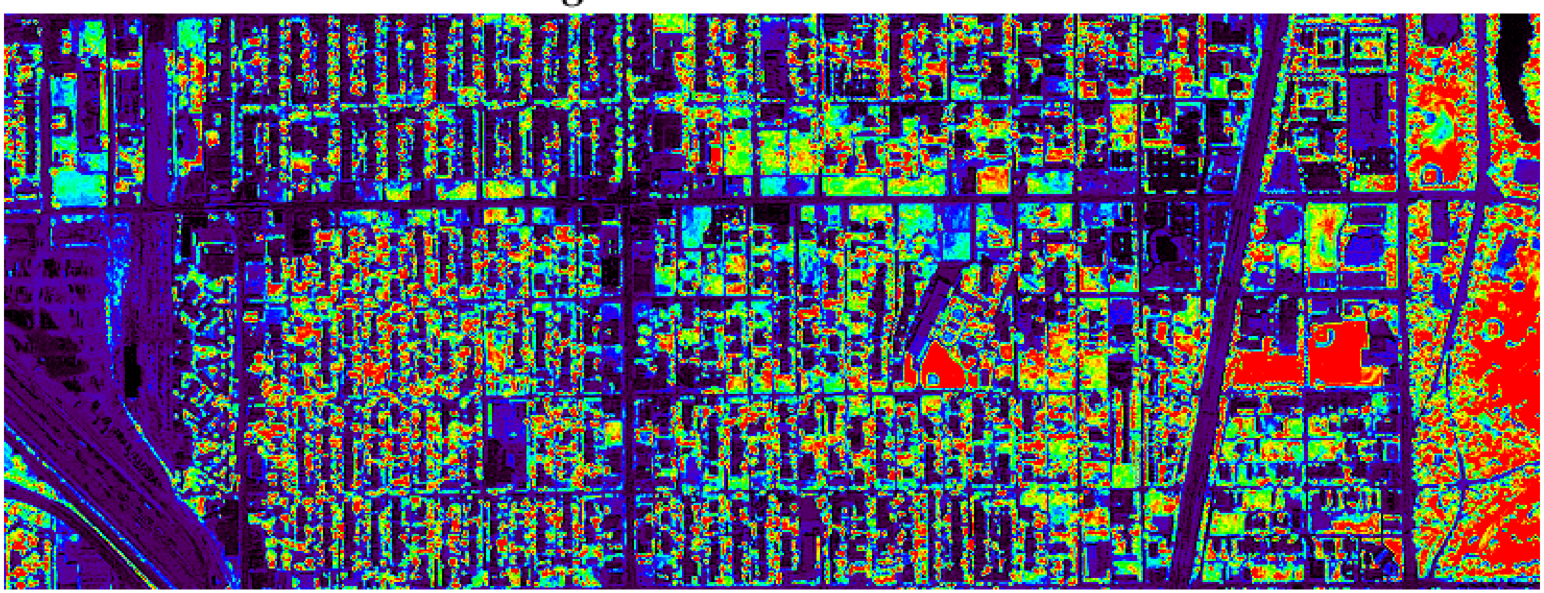


Urban Vegetation Mapping

Chicago, Illinois 9/27/00

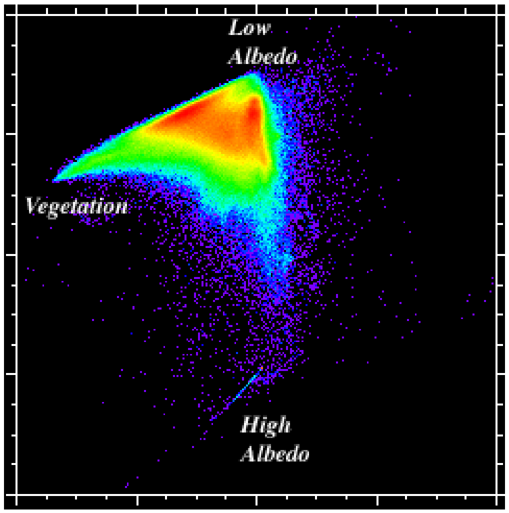


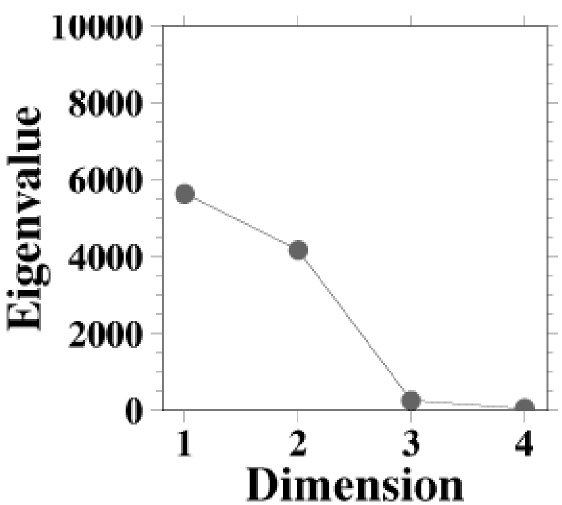
Vegetation Fraction 0 - 50%

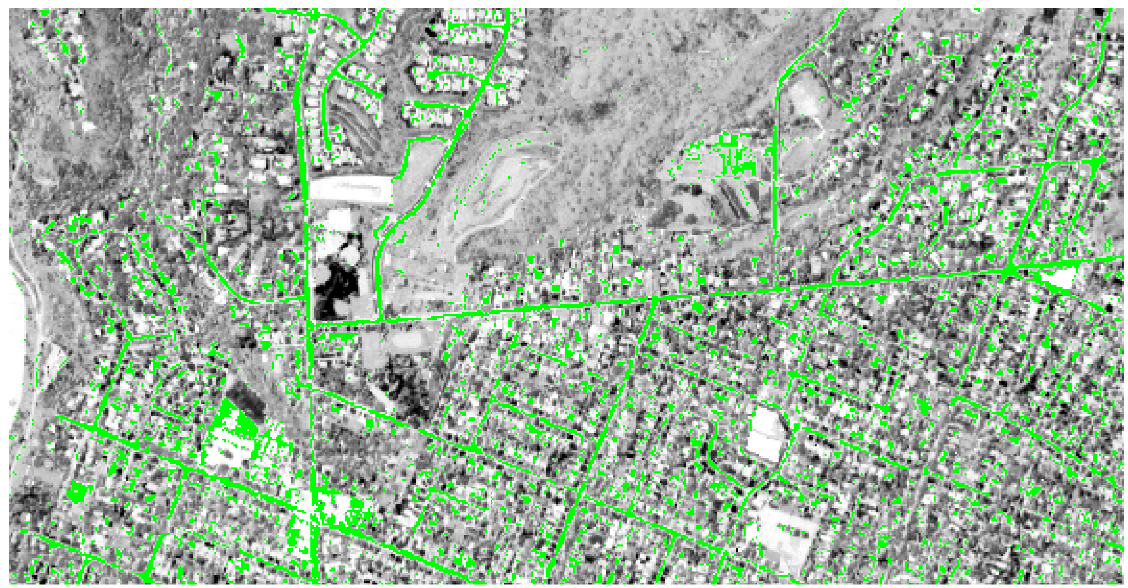


Urban Feature Extraction

Pasadena, California 6/24/01

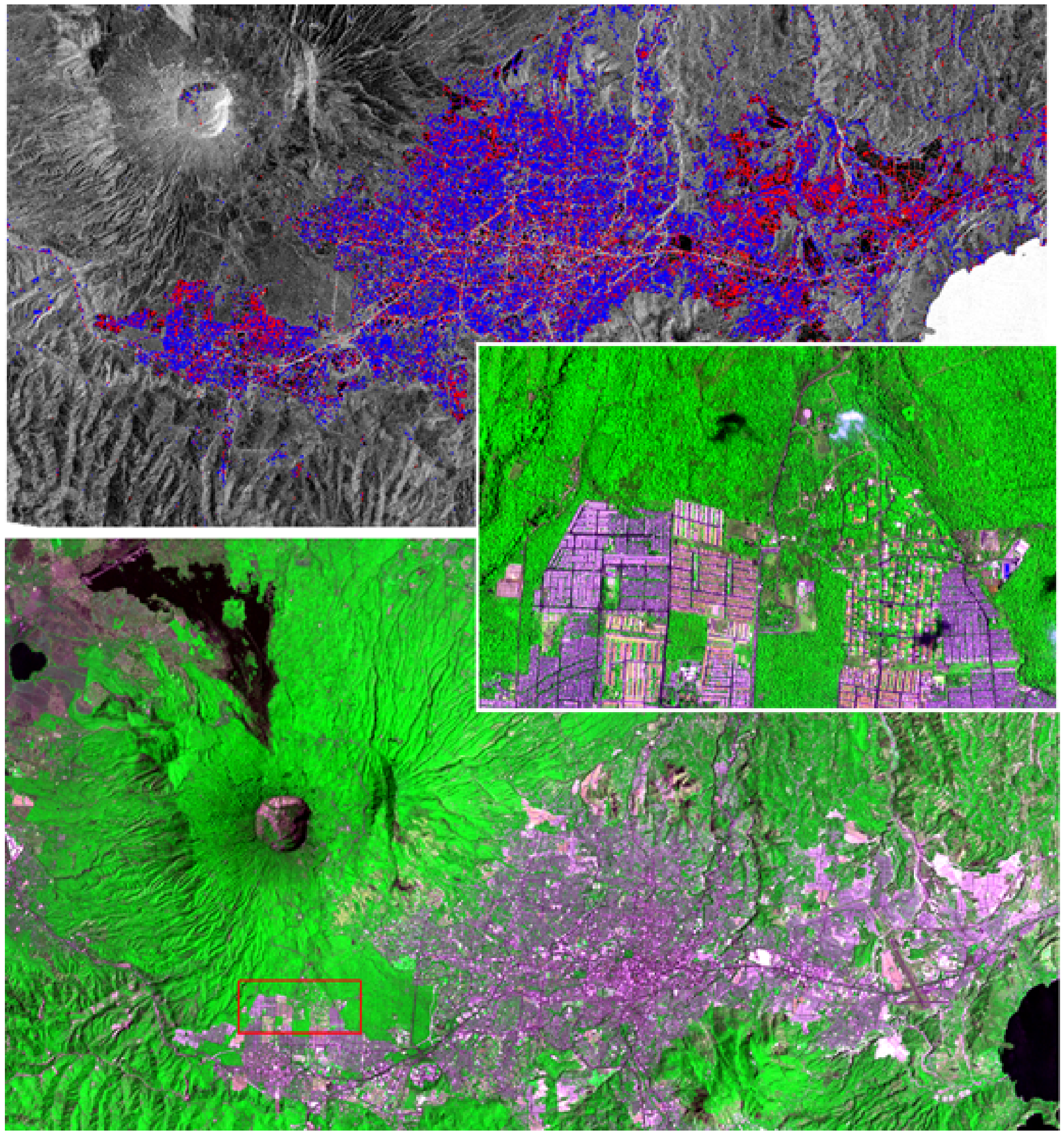






Urban Classification

San Salvador 2000



Conclusions

A wide variety of urban areas worldwide show similar mixing space characteritics (topology and dimension).

All cities investigated were spanned by High Albedo, Low Albedo and Vegetation endmembers within the primary 2D mixing space.

Spectral mixing is predominantly linear among the 3 primary endmembers. Nonlinear in higher dimensions.

Mixing becomes increasingly linear at higher vegetation fractions.

Nonlinear mixing occurs primarily in association with higher proportions of High Albedo endmembers.

Ikonos resolves subtle spectral distinctions among endmembers.

More Information: *www.LDEO.columbia.edu/~small/Urban.html*